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Consuming music through subscriptions - how lock-in effects impact consumers' decisions.

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Abstract

Technological developments and changes in consumer demand have resulted in music streaming being one of the most common ways for people to consume music. Due to these developments having taken place recently, consumer behaviour in the music streaming industry has not thoroughly been studied yet. This paper therefore aims to identify how lock-in effects affect consumers' decisions between subscription plans and their intention to switch between platforms. Through the use of a discrete choice experiment and linear regressions, evidence is found for the presence of switching barriers in the form of loss costs. Meanwhile, personal network externalities affect the decision between contracts but do not incentivize consumers to switch platforms.

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I. Introduction

Technological developments and changes in consumer demand have given rise to an online subscription economy and have resulted in an increasing amount of companies in the media and entertainment industry to now offer their content through online contracts. Music for instance is now offered as an on-demand service through platforms such Spotify and Apple Music. Streaming music has in fact become one of the most common ways for people to listen to music (Savage, 2019; Sinclair & Tinson, 2017). For most platforms, users can choose between two payments types. A freemium membership where the usage of the service is free but access to features is limited and revenue for the provider is generated through advertisements, or a paid subscription where the user is charged a monthly fee for full and advertisement free access to all the content and features available.

Though the market is still growing exponentially, entry of already established tech companies does not seem to impact the few incumbents greatly as strategies are more focused on attracting new consumers to the market instead of persuading existing ones to switch services (Riesewijk, 2017). Research has shown that business strategies for markets with subscriptions should actually be adjusted in order to focus on retaining customers and building long-term relationships with them instead of putting the focus on continually attracting new customers (Reinartz & Kumar, 2003; Sadighi, Ghobadi & Matikolaee, 2015). It is in fact not the high frequency buyer that is most profitable for the firm, since this is most often a variety-seeking type that only adds to short term cash flows. As existing consumers are thus of high value, businesses develop strategies that bind consumers to them (Sadighi et al., 2015). Associating a product or service with network effects and switching barriers is a way of locking consumers in as it limits the mobility of consumers across firms (Farrell & Klemperer, 2007; Czajkowski & Sobolewski, 2015).

Generally, switching within a market of homogenous goods would not be efficient (Taylor, 2003). However, while the initial concept of on demand music streaming would make the market appear to be for a homogenous service, music streaming platforms have been diversifying their services by developing new features and introducing original content in order to drive growth (Savage 2018; Savage 2019). The development of features that can enforce lock-in effects such as network externalities and switching barriers could be the underlying cause of why strategies of firms in the music streaming industry don't seem to be focussed on reducing consumer mobility. However, due to developments in the market for digital content being relatively recent, this yet remains to be studied. In fact, empirical studies on switching behaviour between subscription services is still limited to several industries only. This paper therefore aims to extend the existing research on contract design and lock-in effects to the industry of music streaming. The following question has been formulated for this purpose:

How does the presence of network externalities and switching barriers affect consumer decision making in the music streaming industry?

More specifically, can the presence of network externalities and switching barriers be identified in the music streaming industry? How much are consumers willing to pay for features of music streaming services that have the potential of enforcing lock-in effects? And, how likely are consumers to actually switch to another music streaming platform?

These questions will be answered by a combination of a discrete choice experiment and linear regressions. The necessary data has been collected through the use of an online survey which was distributed mostly amongst students using snowball sampling.

The paper is structured as follows: section 2 provides a background on the music streaming industry, as well as relevant literature on network externalities and switching barriers. In section 3 the survey design is explained and the methodology

introduced. An overview of the collected dataset is also provided. Section 4 presents the results and an analysis of the results, and lastly, section 5 provides the concluding remarks.

II. Theoretical Framework

Underlying Developments

With internet having become increasingly important in our society, so has e-commerce. In 2018, 1.8 billion consumers worldwide had purchased goods online (Statista, 2020) and it is estimated that about 63% of purchases at least start online (Thinkwithgoogle, 2018). People perceive online shopping as more convenient, especially due to the ease of accessibility of websites (Jiang, Yang & Jun, 2013). Furthermore, the decreased cost of distribution due to the availability of Internet everywhere allows consumers access to a wider range of products in order to meet their desire for variety (Anderson, 2006). The music industry thus had to adjust their business models to meet the new demand for online music consumption.

Along with these developments, there is a shift in preference of ownership of goods to access to goods (The Economist, 2013). The speed of technological innovation has made it increasingly costly to keep up with the newest updates and improvements of products, which makes it more attractive for consumers to be supplied on demand and not have to make the necessary capital investment. The implications that follow for the music industry, is a replacement of the traditional physical collecting of music by, previously, illegal downloads, and now increasingly so, streaming (Hagen, 2015).

However, while music streaming may only add to the disappearance of physical collections of records and CDs, it has also been suggested that “streaming services may be the missing link between the music industry and the digital revolution” (Nguyen, Dejean & Moreau, 2013) as the rise of the industry seems to enhance attendance of live music performances and simultaneously battles music piracy.

Network Externalities

Network effects are found in industries where consumers value compatibility with others using the same product or service as this allows them to interact (Farrell & Klemperer, 2007). Once a firm in a market with network effects has been able to capture a great share of the market, it will be hard for new firms to attract demand since consumers derive utility from the fact that other consumers have chosen the same product or service. The IT industry especially is an environment where network effects have proven to be important (Maicas & Sese, 2011). Developments in social media platforms for instance, have generated an environment where consumers easily interact with each other. Indeed, in IT markets the scale of present network effects influences consumers' purchase decisions, with the result that a product with a lower performance rating may in fact capture a larger market share if it has a stronger network (Frels, Shervani & Srivastava, 2003).

Research has recognized a specific type of network effect, namely personal network effects, where the benefits derived from network effects is not homogeneous for every consumer. One derives a higher utility when someone from their personal network, say a friend or a family member, uses the same product or service than when a stranger does (Maicas & Sese, 2011). For social network sites for instance, peer pressure and recommendations made by friends specifically are among the top reasons for people to switch to another service provider (Wu, Tao, Li, Wang & Chiu, 2014), pointing to the positive personal network externalities related to this industry. While the service that comes with being subscribed to a music streaming platform can be enjoyed individually, consumers in this market may derive a higher utility when others from their own personal network use the same service. Music streaming services allow for efficient content sharing with others only within the same platforms. Taking Spotify as an example, users get access to playlists made by friends, are able to see what their friends are listening to and when sharing songs through social media networks the recipient will receive a link to the song on Spotify.

Switching Barriers

Switching barriers or switching costs refer to the perceived economic and psychological costs consumers face when changing between alternatives (Jones, Mothersbaugh & Beatty, 2002). Switching costs may make consumers refrain from switching and may arise due to familiarity with how a certain product operates or termination costs that are associated with switching (Klemperer, 1987). While switching costs are often represented in the form of cancellation costs when terminating a contract, such costs need not be monetary. Other research has previously identified loss costs as a type of switching barrier and found a strong association with consumers' repurchase intentions and resistance to change service providers (Jones et al., 2002; Perera & Kim, 2002). Loss costs refer to the perception of benefits and privileges that are lost when switching to an alternative provider and are specific to the service. Similarly, Kahneman and Tversky (1979) identified the concept loss aversion, which has been a very important contribution to decision-making theory. Their study showed that people tend to prefer the avoidance of losses over the collection of gains.

In the case of music streaming, consumers lose out on several benefits when switching from provider which may thus make them reluctant to switch. Firstly, the music recommendations given on the platforms that are based on prior usage. Secondly, consumers have the opportunity to create value within a music streaming application by creating personal playlists. Generally, the customization and the perceived contribution a consumer has towards the final product or service enhances preference fit and a consumer's utilitarian benefit (Kirk, Swain & Gasgain, 2015). The more time is spent managing playlists, the more valuable they become to the user (Hagen, 2015). Created playlists cannot be directly transferred to another platform, this may thus function as a loss cost and form an incentive for consumers to remain with their status quo. Likewise, consumers may be more willing to choose a subscription plan when an option for playlists transferability is included.

III. Data and Methodology

Survey Design

The research for this paper is an adaptation of a study conducted by Czajkowski & Sobolewski (2015) on consumer behaviour and sources of consumer lock-in with regards to mobile telephone subscriptions. Data was collected by the use of a survey. The survey was distributed through email and instant messaging platforms and snowball sampling was employed in order to recruit a larger number of respondents. The survey consisted of two parts, excluding a final section with demographic questions.

The first part posed several questions on the participants previous experience with music streaming services, all with the aim of getting insight into the sample. Participants were asked whether they are or have been subscribed to a music streaming platform and if so, how this is or was paid for. Furthermore, participants who have experience with music streaming were asked to rate their satisfaction with the platform they used on a 7-point Likert scale and whether they had ever considered switching to another service provider. The last question of this part asked the participants how important they perceive each of the aspects that were later represented in the ultimate experiment to be.

Subsequently, in the second part the participants were presented with 6 choice sets showing different hypothetical music streaming subscription plans. For each choice set, respondents were asked to choose one of the three presented profiles. After choosing from the choice set participants were asked whether they actually prefer the chosen plan over their current way of listening to music. The status quo alternative, which is when consumers choose to stick with a current situation or previous decision taken, has been identified to be a relevant alternative in decision making (Samuelson & Zeckhauser, 1988). An example of a choice set presented to respondents is depicted in Figure A.

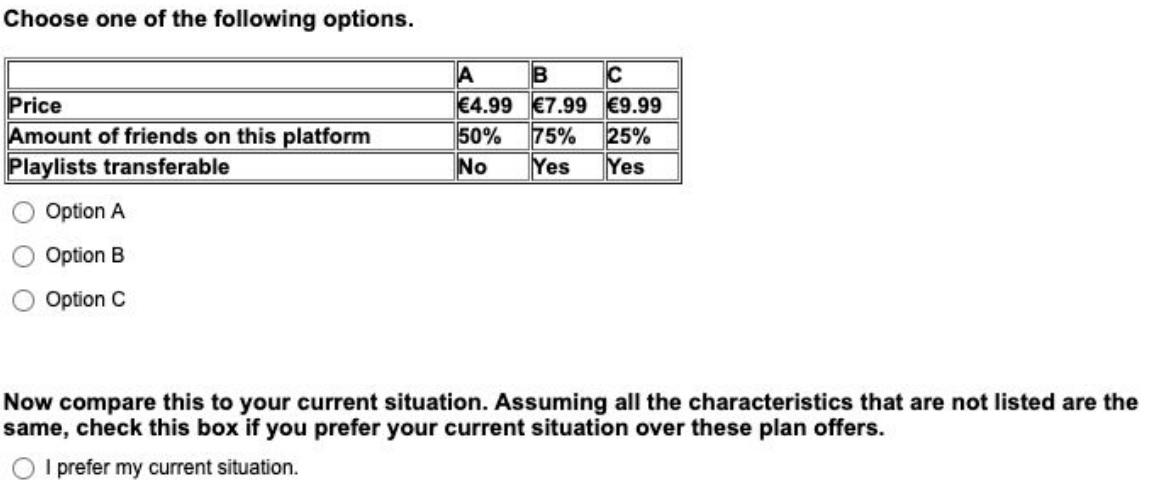

Figure A. An example of a choice set presented in the survey

Each profile in the choice set differs with respect to three attributes that in turn consist of either two or three levels. An overview is provided in Table 1.

Table 1. Overview of the attributes and respective levels.

Price	Network	Playlists transfer
€4.99	25%	Yes
€7.99	50%	No
€9.99	75%	

The attribute for price has three levels, which have been decided upon based on the price levels of the biggest music streaming platforms. Platforms such as Spotify, Apple Music, Youtube, Deezer and Tidal all offer their standard premium subscription plan at €9.99. Moreover, Spotify and Apple Music offer a cheaper plan specifically for students, priced at €4.99. Some providers also offer a plan priced in between those. Amazon Prime Music and Amazon Music Unlimited for instance offer memberships for a monthly fee of €7.99. While some platforms also have more expensive memberships, these are not included in the survey as such packages, which are often family accounts, are likely less relevant to students. Furthermore, as the willingness to pay will be measured according to this attribute, the possibility of a

freemium subscription has been left out as well. The attribute for network externalities is depicted as the amount of friends, in percentages, that use the platform for which the hypothetical subscription plan is offered. The levels are based upon the research done by Czajkowski & Sobolewski (2015). The attribute of playlist transferability is related to the potential presence of loss costs.

The experiment design has been done according to the shifting strategy introduced by Bunch, Louviere and Anderson (1996). As a priori information is lacking, ease of the survey has been chosen over a statistical advantage that a larger design would provide (Lusk & Norwood, 2005). Shifting starts from the original column with attributes. Consequently, for each new alternative created, each level of the attributes is increased by one until the cycle is completed. The method ensures minimal overlap of the levels per choice set and an occurrence of all combinations necessary to measure the main effects of the experiment (Zwerina, Huber & Kuhfeld, 1996). The design is constructed in a way that is optimal for experiments with asymmetric attributes (Burgess & Street, 2005). The codified design can be found in Table 1A in the appendix.

Descriptive Statistics

In total, 95 fully completed responses were collected. Of all participants 71.58% are female, and 85.26% are students. Furthermore, 85.26% reported that they use a music streaming service, 4.21% of the participants reported they have been subscribed to a music streaming service in the past but were not at the time of the survey, and the remainder reported to not have been subscribed at all.

The distribution of all participants who have used a music streaming service and the respective payment options that were presented in the survey are presented in Table 2. As can be seen, most respondents make use of a premium account that they either pay for themselves or have someone else pay for. The high share of students who use an account that is paid for by someone other than themselves may point to their price sensitivity where they either simply use someone else’s account or perhaps have their parents pay for it.

Table 2. Overview of payment types and reported employment status.

	Account payment		
	Freemium account	Paid account	Paid for by someone else
Student	7 (9.09%)	32 (41.56%)	38 (49.35%)
Employed	0 (0.00%)	5 (83.33%)	1 (16.67%)
Unemployed	0 (0.00%)	1 (100.00%)	0 (0.00%)
Other	1 (100.00%)	0 (0.00%)	0 (0.00%)

Table 3 presents an overview of the reported levels of importance with regards to the same three aspects that were included in the hypothetical plans in the survey. This question was only presented to respondents who had (previously) used a music streaming service. It appears that for the majority of these participants, 83.16%, the level of the price of a music streaming service is at least considered to be *very important*. The preferences with respect to being able to transfer playlists seems to be much more evenly distributed. Meanwhile for more than half of the respondents, 50.53%, the amount of people from their network that use the same platform is *not at all important*. This may imply that people do not place great importance to being able to share content efficiently with friends or, more generally, do not seem to mind how many of their friends use a certain platform when deciding which to choose for themselves.

Table 4 shows the results from the question presented to those who have used a music streaming platform, on whether the respondent was satisfied with the platform used and whether they have ever considered switching. As can be seen, 82.35% have never considered switching and for those who have, this did not seem to be due to a high level of dissatisfaction with the service.

Table 3. Overview of attributes and reported importance levels.

	Price	Network	Playlists transfer
Not at all important	0 (0.00%)	48 (50.53%)	9 (9.47%)
Slightly important	2 (2.11%)	21 (22.11%)	12 (12.63%)
Moderately important	14 (14.74%)	15 (15.79%)	24 (25.26%)
Very important	50 (52.63%)	10 (10.53%)	27 (28.42%)
Extremely important	29 (30.53%)	1 (1.05%)	23 (24.21%)

Table 4. The reported level of satisfaction with a platform according to whether switching has previously been considered.

	Have you ever considered switching to another platform?	
	Yes	No
Extremely dissatisfied	0 (0.00%)	5 (100.00%)
Moderately dissatisfied	0 (0.00%)	3 (100.00%)
Slightly dissatisfied	2 (100.00%)	0 (0.00%)
Neither satisfied nor dissatisfied	1 (100.00%)	0 (0.00%)
Slightly satisfied	1 (50.00%)	1 (50.00%)
Moderately satisfied	7 (19.44%)	29 (80.56%)
Extremely satisfied	4 (11.11%)	32 (88.89%)
	15 (17.65%)	70 (82.35%)

Methodology

A discrete choice experiment will be conducted first. A mixed logit (MXL) model is constructed so that the correlation between the choices made can be assessed. A MXL regression will then be run where the random coefficients are assumed to be normally distributed. The model takes the heterogeneity of the population into account as the parameters are assumed to vary across individuals. Having presented participants with several combinations of plan options gives the following utility function:

$$U_{utility\ of\ participant\ i\ from\ choosing\ alternative\ a} = \beta_{price} price + \beta_{network} network + \beta_{playlistloss} playlistloss + \varepsilon_{ia}$$

where
price is a continuous variable,
network is a continuous variable,
playlistloss is a dummy variable that equals 1 when the subscription plan does not include an option for playlists to be transferred along, and 0 otherwise.

Given the variables that will be examined, the results will show how consumers choose from the set of options. While the absolute values of the estimated coefficients cannot be interpreted, the results will indicate how a variable affects the probability that a plan is chosen. This will thus provide an answer to the question of how each attribute affects consumers' willingness to choose a certain plan.

Besides this, the MXL model allows for the average respondent's willingness to pay for each attribute to be calculated. It is computed as the marginal rate of substitution between price and the attribute levels for playlists and network and will thus provide a monetary value that shows how much the presence of friends and family on the network and the possibility of transferring playlists is worth to the participants.

Another approach is included in order to account for the respondent's actual willingness to switch. Two linear regression will be run on the dependent variable status quo. This is a dummy variable that equals 1 if the respondents still prefered their current situation after facing a choice set, and 0 otherwise. These regressions will not contain all the alternatives previously included in the MXL model. Instead only the alternative the respondent actually chose, and thus also compared to their current situation, is included.

First, a regression will be run with the independent variable satisfaction. This variable indicates the reported level of satisfaction with the music streaming platform the consumer has used and this will therefore give insight as to whether the respondent's satisfaction has an effect on actually choosing to take a new contract. This yields the following regression equation:

$$statusquo = \beta_0 + \beta_1 satisfaction_i + \varepsilon_i$$

Then a regression will be run on the independent variables price, network and playlist loss in order to examine to what extent these attributes affect a consumer's decision to actually switch. This leads to the final regression equation:

$$statusquo = \beta_0 + \beta_1 price_i + \beta_2 network_i + \beta_3 playlistloss_i + \varepsilon_i$$

IV. Results

Mixed Logit Model

Due to each of the participants having been presented with 6 choices consisting of 3 alternatives, the estimated MXL model consists of 1710 observations from 570 choice sets. The results are given in Table 5 and allow for the assessment of the coefficients' significance, sign and relative value to each other.

The means for each the coefficients are found to be significant. The estimated coefficient for the attribute of price is -1.31, indicating, intuitively, that when there is an increase in price of a subscription plan the likelihood that this plan is chosen decreases. The positive coefficient for network implies that, on average, an individual is more likely to choose a platform when a greater amount of his or her friends are subscribed to the same platform. This thus provides an indication of the presence of personal network externalities in the music streaming industry**.** As for the attribute related to playlist transferability, a negative coefficient is estimated. This suggests that when a plan does not have the option for playlist transfer, individuals are on average less likely to opt for that plan. However, heterogeneity amongst consumers can be observed, especially with respect to playlist loss. The high estimation of the standard deviation for the respective coefficient shows that while most of the consumers are indeed less likely to choose a subscription plan when the option of transferring playlists lacks, some will actually be more likely too. This heterogeneity is somewhat in line with the difference in reported levels of importance of playlist transferability seen previously.

Table 5. Results of the MXL model for respondent's music streaming plan choices.

	Parameters	
Variables	Mean	Standard Deviation
Price	-1.308*** (0.372)	0.697 (0.302)
Network	0.593*** (0.226)	0.256 (0.464)
Playlists loss	-3.300*** (0.940)	3.356 (1.121)
Log simulated likelihood	-310.429	
Wald chi²	12.69	
Prob > chi²	0.005	
Observations	1710	
Cases	570	

Notes: Standard error in parentheses.
* p-value < 0.1 , ** p-value < 0.05, *** p-value < 0.01

Willingness To Pay

Subsequently, the marginal willingness to pay is calculated. As can be seen in Table 6, consumers are willing to pay and extra €0.45 for having all of their friends (100%) use the same platform.

On the other hand, consumers are seemingly willing to pay -€2.52 when playlists cannot be transferred along. This result again suggests that consumers prefer the presence of such a feature over the absence of it. If such a feature were not to be included with a music streaming subscription plan, consumers would thus have to be compensated for it by a reduction in price.

Table 6. Marginal willingness to pay for music streaming service attributes.

		95% confidence interval	
	WTP	lower level	upper level
Network	0.453	0.228	0.678
Playlists loss	-2.523	-2.988	-2.058

Notes: measures are expressed as an increase of price in euros.

Linear Regressions

The results of the regressions ran on the dependent variable status quo are presented in Table 7.

Model 1 contains the results from the regression ran with the independent variable satisfaction. Only 510 observations are included in this model as this was only relevant for those respondents who indicated that they had used a music streaming service. This comes down to 85 participants. As can be seen from the results, the estimated coefficient for satisfaction has not been found to have a significant effect. As expected however, the relationship between the two variables is positive which would indicate that a higher satisfaction increases the likelihood that consumers refrain from switching.

Model 2 contains the results obtained from the regression with independent variables price, network and playlist loss. A significant coefficient is found for price. Hence, a one euro increase in price would result in the probability of someone choosing to remain with their status quo to increase by 0.045. No significant effect is found for the variable network though the negative coefficient does seem to be in line with the suggestion that a higher amount of friends using a certain platform will make this platform more attractive to a consumer, thus reducing the likelihood that this consumer sticks to its status quo. Lastly, the likelihood that a consumer refrains from switching increases by 0.219 when playlists cannot be transferred along. This effect is also found to be significant but nonetheless the standard error for price is smaller than that for playlist loss, indicating less irregularities in the data.

Table 7. Linear regression estimates of the determinants of status quo.

	(1)	(2)
Variables	Model 1	Model 2
Satisfaction	0.012 (0.012)	
Price		0.045*** (0.013)
Network		-0.027 (0.024)
Playlists loss		0.219*** (0.043)
Constant	0.584*** (0.078)	0.359*** (0.090)
Observations	510	570
R-squared	0.0019	0.051

Notes: All columns report coefficients from the regression run on the dependent variable status quo.
Standard errors in parentheses
* p-value < 0.1 , ** p-value < 0.05, *** p-value < 0.01

V. Conclusion

Discussion

Enforcing or encouraging lock-in effects such as network externalities and switching barriers would allow firms to limit consumer mobility within a market. However, while research has been conducted on both of these lock-in effects, this has not yet been extended to the relatively new industry of on-demand music. Therefore, this paper examines the presence lock-in effects in the music streaming industry. Through a combination of a discrete choice experiment and linear regressions the impact of network externalities and switching barriers on consumer behaviour is analyzed. This allows for the following question to be answered:

How does the presence of network externalities and switching barriers affect consumer decision making in the music streaming industry?

The estimated MXL model controls for the attributes of price, the presence of friends on a certain music streaming platform, and the possibility that personal playlists may be lost when committing to switching to a new platform. As the results of the model indicated, both network and loss of playlists have a significant effect on the way consumers choose between different contracts.

A greater number of friends using an alternative platform increases the likelihood that consumers opt for a subscription to that platform and simultaneously, consumers are willing to pay more for a higher number of friends present. However no evidence was found for it to have an effect of actual willingness to switch. Moreover, more than half of the respondents had indicated not to place any importance to this aspect.

As for switching barriers, the MXL model indicated that when a subscription plan does not allow for playlists to be transferred along it negatively impacts the likelihood

that consumers choose the respective plan. This results in a negative willingness to pay on behalf of the consumers, implying that they would need to be compensated by a reduced price when this is the case. In addition, as the regression results showed, consumers are more reluctant to actually switch when playlists will be lost.

In order to formulate an answer to the previously raised question, this paper has identified the presence of network externalities and switching barriers in the music streaming industry. While switching barriers in the form of loss costs certainly seem to have the potential of increasing customer retention, personal network effects are taken into account by consumers when choosing between subscription plans but the current value that these bring about does not seem to be sufficient to actually convince consumers to switch providers.

Implications

This study has several implications for firms operating in this market that wish to increase their customer retention. First, this paper has not provided evidence for the relevance of network externalities in this industry. However, further development and improvement of features that can enhance the effect of network externalities might change this. Moreover, while approximately half of the respondents reported that the presence of friends on the same platform was not at all important to them, some heterogeneity could be observed. Preferences for the presence of friends on the same platform might thus differ according to certain groups within the population. Second, firms should continue to develop and improve features that will result in loss costs for consumers when they switch. While this paper has only devoted attention to the impact of value creation through personal playlists, there may be other possibilities. An example is to increase the benefits that come from the data that is collected on prior usage. Accordingly, such features, related to network externalities and switching barriers, will both diversify the company's service as well as create incentives for consumers to refrain from switching to an alternative provider.

Limitations

The research conducted in this paper is limited in the sense that the data sample used was small and not representative of the population. The employment of snowball sampling may have resulted in sampling bias, as most of the respondents to the survey were students of the same age and gender category. Extending this experiment design to a larger scale may ensure a more externally valid study. Moreover, the conducted experiment may be improved upon by collecting a priori information through a pilot survey. The experiment design would then not be bounded to a shifting strategy but can instead achieve statistical efficiency by maximum accuracy of the estimates of the parameters. This again calls for the research to be conducted on a larger scale so that the number of choice sets presented to participants is not as limited.

Further research on a larger scale can provide extra insights into the previously mentioned implications by controlling for more aspects in the MXL model. Attributes related to other potential lock-in effects should be included and another attribute that may be interesting to include is brand popularity. Incorporating this as an alternative-specific constant also allows for case-specific constants to be included, which will show how demographic traits are related to consumers' choices. Finally, making the survey more extensive by adding questions on participants' status quo situation will make it possible to actually add the status quo dummy to the utility function.

Appendix

Table 1A. The codified main-effects experiment design.

Set	Alternative	Attributes		
		I	II	III
1	A	0	0	0
	B	1	1	0
	C	2	2	1
2	A	0	1	0
	B	1	2	1
	C	2	0	1
3	A	1	2	0
	B	2	0	0
	C	0	1	1
4	A	1	0	0
	B	2	1	1
	C	0	2	1
5	A	2	1	0
	B	0	2	0
	C	1	0	1
6	A	2	2	0
	B	0	0	1
	C	1	1	1

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